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Spatial Clustering of Urban Villages on Stunting Babies Data in Samarinda Using the DBSCAN Model

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ABSTRACT

The government has set an annual target to reduce stunting rates. To achieve this, the Health Department must implement well-targeted policies based on a prioritized approach, ensuring that interventions are comprehensive and coordinated for maximum effectiveness. This study aimed to cluster urban villages in Samarinda based on stunting data, including the number of cases, baby weight, and height, using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) model. The optimal model was selected by determining the highest silhouette score from various combinations of epsilon (ε) and MinPts values. The best results were obtained with ε = 0.95 and MinPts = 3, which produced a silhouette score of 0.432. The clustering process resulted in the formation of two primary groups, whereas four villages remained unclustered, exhibiting significant variations in the number of stunted babies. Additionally, spatial analysis revealed that stunting and malnutrition were more prevalent in densely populated urban areas, emphasizing health risks associated with population density. These findings not only provide a clearer understanding of the spatial distribution of stunting in Samarinda but also highlight the need for targeted, area-specific interventions. The insights gained from this study offer a valuable basis for prioritizing public health initiatives and developing data-driven policies to effectively address stunting in Samarinda.

INTRODUCTION

Stunting is a concern in all countries including Indonesia. Recognizing the importance of child welfare and commitment to the 2030 Sustainable Development Goals (SDGs) program, Indonesia has made various efforts to overcome stunting. According to the United Nations International Children's Emergency Fund (UNICEF) 2020 report, Indonesia is ranked as the fifth country with the highest number of stunted children. Through the *Rencana Pembangunan Jangka Menengah Nasional (RPJMN)* for the 2020-2024 period, the President also showed his commitment by making the elimination of stunting a top priority. This indicates that Indonesia is serious in dealing with stunting and providing a brighter future for the nation's next generation.[1]

The World Health Organization (WHO) in 2015 defined stunting as impaired growth and development of children due to chronic malnutrition and repeated infections, characterized by height or length below the standard. This definition was changed by WHO in 2020. Stunting refers to a short or very short category based on height or length for age, which is less than -2 standard deviation on the WHO growth curve. This condition occurs due to irreversible conditions caused by insufficient nutrient intake and repeated chronic infections that occur in the First 1000 Days of Life for babies. Many aspects are seriously affected by stunting cases. In terms of health aspects, namely experiencing cognitive and motor development obstacles (growth failure), and metabolic disorders in adulthood. In term of economic aspect, the country experiences annual losses from the Gross Domestic Product (GDP) indicator.[2]

The government aims to decrease the stunting rate every year. Various efforts have been made to ensure the success of this program. In 2022, the Ministry of Health provided blood supplements for adolescent girls, and additional food for pregnant women and children aged 6 to 24 months.[3] Furthermore, the Minister of Health made 11 additional intervention programs to accelerate the reduction of stunting based on three phases, i.e. the phase before childbirth, the phase after childbirth, and the phase across life. The 11 specific intervention programs designed are anemia screening, consumption of blood additive tablets for adolescent girls, antenatal care, consumption of blood additive tablets for pregnant women, supplementary feeding for pregnant women with chronic energy deficiency, baby growth monitoring, exclusive breastfeeding, provision of animal protein-rich complementary food for under-fives, management of babies with nutritional problems, increasing coverage and expansion of immunization, education of pregnant women and families including triggering free open defecation.[4]

A reduction in stunting prevalence rates can support the demographic bonus program in 2045 with high productivity and competitiveness. Stunting can have long-term consequences on children's physical and cognitive development. Stunted children have a higher risk of experiencing growth and development disorders, as well as other health problems in the future. By reducing the prevalence of stunting, the government can ensure that future generations emerge in optimal health and have full potential to contribute to the country's economic development. Children free from stunting have better learning abilities, higher productivity, and a greater likelihood of becoming a competitive workforce in the future. Therefore, investing in improving the nutrition and care of young children will help build a healthy and competitive society, and achieve the goals of the 2045 demographic bonus program.

The Department of Health must conduct policies immediately to be right on target based on a priority scale because it requires comprehensive and coordinated handling in order to ensure policy effectiveness, Efforts to accelerate stunting prevention need to target vulnerable groups of people who are included in high priority areas. In this sense, the Department of Health must collaborate and synergize with Community Health Center *(Puskesmas)* and universities so that interventions can be implemented in an integrated and effective manner.

Determining the priority groups of urban villages can be done using clustering techniques. Some clustering models that can be done are k-NN, k-Means, hierarchical clustering, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN). This algorithm does not force every neighborhood into a cluster. Its ability to identify data as noise (outliers) is valuable, as these outlier neighborhoods may require policy interventions that are unique and different from the clustered areas.[5,6] Furthermore, DBSCAN does not require predetermining the number of clusters, making it more objective in finding natural patterns based on data density.[6] These characteristics make DBSCAN a superior method for generating realistic and actionable clustering of neighborhoods for targeted public health initiatives. Thus, research on applying clustering techniques to data on stunted babies is very suitable for using the DBSCAN model.

Analysis of stunting data using spatial statistics provides valuable insights for policymaking. This approach allows for the identification of spatial patterns and the determination of priority intervention areas. For instance, Sakti et al. mapped and prioritized each district/city in Aceh Province using QGIS on data on the number of LBW incidents, the number of diarrhea cases in children under five, the number of pneumonia cases in children under five, IMD coverage, and exclusive breastfeeding coverage.[5] Riznawati et al. conducted a spatial autocorrelation test on stunting prevalence data in West Java using the Moran index.[6] Gaffar et al. used Support Vector Regression to predict provincial prevalence rates in Indonesia.[7] Revildy et al. predicted the prevalence of stunting using the Spatial Error Model based on the percentage of poor people, the average length of time the population over 25 years of age has been in formal education, the proportion of early breastfeeding initiation, the proportion of complete basic immunization, the prevalence of chronic energy deficiency, the proportion of children under 24 months who have been breastfed, the proportion of children aged 6 to 59 months who receive supplementary feeding, the percentage of food management sites, and the percentage of proper sanitation.[8] Cholid et al. created a prediction model for the percentage of stunted babies based on the percentage of complete immunization and the percentage of pregnant women at risk of chronic energy deficiency using the Geographically Weighted Regression model.[9] Furthermore, Retnaningsih et al. mapped the indicators of stunting babies, i.e. the percentage of complete immunization, the percentage of early breastfeeding initiation, the percentage of use of family planning tools, the percentage of access to proper sanitation, the percentage of proper drinking water, the percentage of poor people, and the percentage of pregnancies at an early age. The thematic map produced using ArcView was obtained from clustering results using hierarchical cluster analysis.[10]

This study used cluster analysis like Retnaningsih's but used the DBSCAN model to perform the clustering technique, so it is possible that there are regional data that do not have cluster groups. Of course, regions that do not have cluster groups can be seen as anomalies or special cases because there is not enough evidence to belong to a particular group. Additionally, this study used secondary data collected from all Integrated Health Service Posts/*Pos Pelayanan Kesehatan Terpadu (Posyandu)* in Samarinda City, obtained through the Samarinda City Health Office. Therefore, this research aimed to cluster urban villages in Samarinda based on stunting data for babies, considering the number of cases, weight, and height using the DBSCAN model.

MATERIAL AND METHOD

This research was a quantitative study that used numerical data that could be measured objectively and analyzed using a ratio data scale. The data used in this study were secondary data taken from Integrated Health Service Posts/*Posyandu* records in all urban villages of Samarinda. This data was obtained from the Samarinda City Health Office for the year 2023, and includes information on the height and weight of stunted babies.

The population in this study was all stunted babies under 1000 days of life in Samarinda City, recorded at each Integrated Health Service Posts/*Posyandu* from August 2022 to July 2023. This study used aggregate data at the urban village level. The approach used in sample selection is a saturated sample, where all available data from the population will be processed and analyzed. Thus, this study used all data on stunted babies without random sampling.

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) models will be used for clustering. Two key parameters in DBSCAN are epsilon (ε) and MinPts (minimum number of points). These parameters will be determined by finding the value that maximizes the silhouette score, which measures how well the data has been clustered. Euclidean distance is used to calculate the similarity between data points.

After the clustering process, the groups of data will be described to provide insight into each cluster's characteristics. This involved analyzing the distribution of stunting cases, weight, and height among babies in each cluster. For visualization purposes, each urban village was represented in a scatterplot based on its stunting attributes, which include the number of cases, average weight, and average height of babies.

Based on the clustering results, the clusters will be sorted based on the priority level of handling. This priority order will be based on the results of the DBSCAN analysis, considering the severity and number of stunted babies in each cluster. Village priorities were determined based on the number of stunted babies, followed by their weight and height. Data on the number of stunted babies was transformed using the Cox box method.

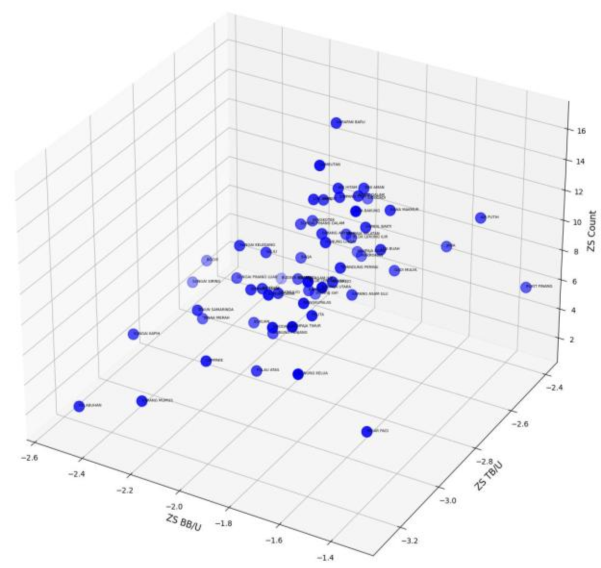
To visualize the results of the spatial analysis, a thematic map will be created using QGIS version 3.34. This map will map the distribution of stunted babies in each urban village in Samarinda City. The spatial data used comes from Shapefile (SHP) files that contain the administrative boundaries of urban villages in the city.

RESULTS

This study focused on babies in the first 1000 days of life or 1000 *Hari Pertama Kehidupan (HPK)*. From 15594 recorded babies, 9720 were eligible for the 1000 *HPK* criteria, and after removing duplicates, 4880 samples remained. By using the cox box method, the lambda value=0.4237≈0.5 was obtained. Therefore, the data on the number of stunted babies was transformed using the root function, creating the ZS count variable. The average weight and height of babies in each urban village were calculated and then transformed using Z Score.

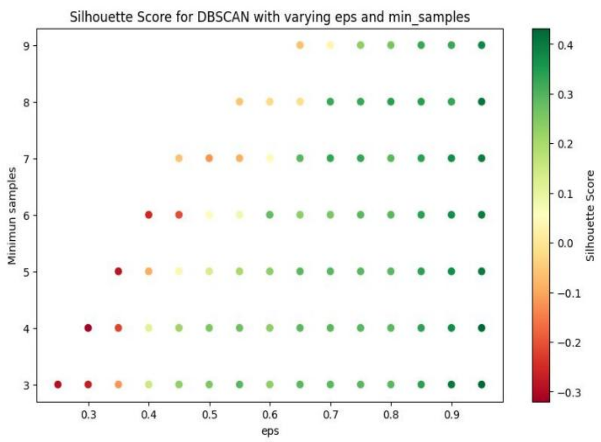
The visualization for research data can be depicted through a scatterplot as shown in Figure 1. It can be seen that some of these urban points were clustered together while others were spread further apart. Through this visualization, it was clear that Harapan Baru village, which does have the highest number of stunted babies, was far away from the cluster that would be formed.

A proper DBSCAN model is constructed by having the right parameters. In this study, ε and MinPts were selected using grid search. The silhoutte value from data were computed based on different ε and MinPts values, i.e. ε values were in the range of 0.2 to 1.0 while MinPts were in the range of 3 to 9. Based on Figure 2, the highest silhouette value was achieved when ε =0.95 and MinPts=3. This highest silhouette value was 0.432.



Source: Seconday Data Analysis from Integrated Health Service Posts/*Posyandu* of Samarinda, 2023

Figure 1. Visualization Data Using Scatterplot



Source: Seconday Data Analysis from Integrated Health Service Posts/*Posyandu* of Samarinda, 2023

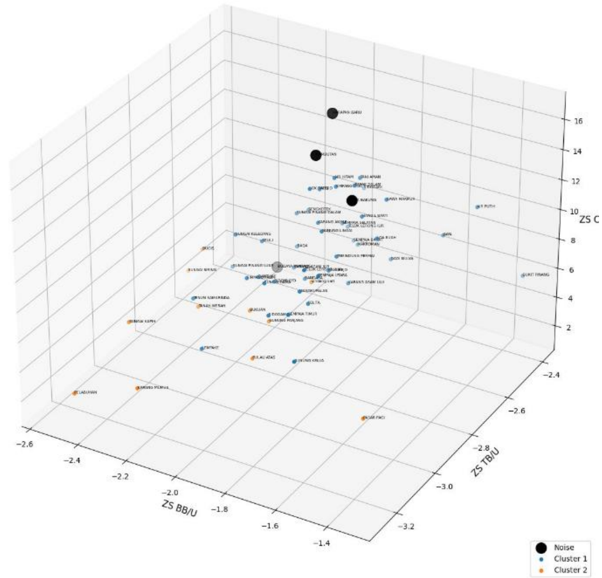
Figure 2. Silhouette Score Based on ε and MinPts

The DBSCAN model was obtained after determining the appropriate ε and MinPts values. Based on Figure 3, the number of clusters formed was 2 groups, with 4 other villages not having clusters (i.e. Pampang Culture, Harapan Baru, Loa Bakung, Sambutan). However, the villages that did not have clusters showed significant differences in the number of stunted babies.

More information regarding the clustering results using the DBSCAN model was presented in Table 1. Harapan Baru, Sambutan, and Loa Bakung were the top 3 areas with the highest cases of stunted babies. This is in stark contrast to the result that Budaya Pampang was the area with the lowest cases of stunted babies. However, the Budaya Pampang area has cases with a very alarming average weight and height.

Spatially, the mapping of urban villages using the DBSCAN model is provided in Figures 4, 5, and 6. Based on Figure 4, it was clear that, spatially, the villages of Harapan Baru, Sambutan, and Loa Bakung were the three areas in the center of Samarinda with the highest cases of stunted babies.

The spatial distribution of stunting cases in practically all urban settlements in the heart of Samarinda city was effectively depicted on the map in Figure 5. The location with favorable socioeconomic or environmental characteristics was referred to as Group 1. The areas of 44 urban villages that make up group 1's total area were larger than half of Samarinda. Ninety babies each subdistrict were on average listed as cases of stunting.



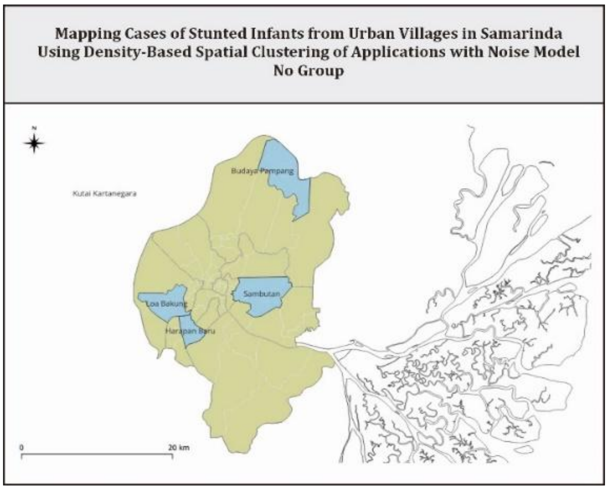
Source: Seconday Data Analysis from Integrated Health Service Posts/*Posyandu* of Samarinda, 2023

Figure 3. Illustration of Urban Village Clustering

Table 1. Clustering Results Using DBSCAN Model

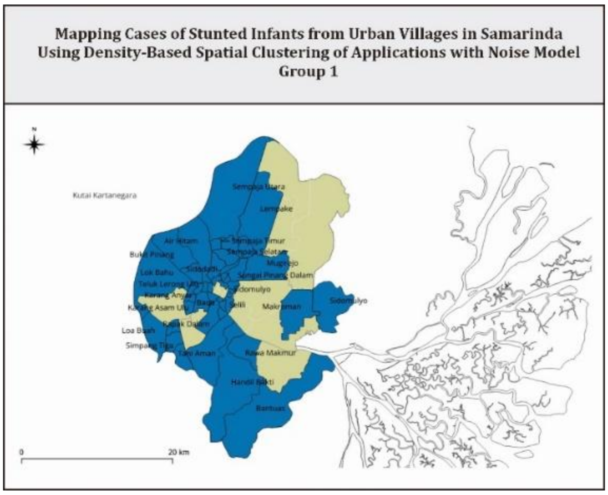
Priority	Group of Urban Villages	Mean Count	Mean Weight	Mean Height
1	Harapan Baru	278	8.10	71.13
2	Sambutan	263	8.17	70.81
3	Loa Bakung	218	7.73	67.71
4	Group 1 (Air Hitam, Air Putih, Bandara, Bantuas, Baqa, Bukit Pinang, Dadi Mulya, Gunung Kelua, Gunung Lingai, Handil Bakti, Jawa, Karang Anyar, Karang Asam Ilir, Karang Asam Ulu, Lempake, Loa Buah, Lok Bahu, Makroman, Mangkupalas, Mesjid, Mugirejo, Pelita, Rapak Dalam, Rawa Makmur, Selili, Sempaja Barat, Sempaja Selatan, Sempaja Timur, Sempaja Utara, Sengkotek, Sidodadi, Sidodamai, Sidomulyo, Simpang Pasir, Simpang Tiga, Sungai Dama, Sungai Keledang, Sungai Pinang Dalam, Sungai Pinang Luar, Tani Aman, Teluk Lerong Ilir, Teluk Lerong Ulu, Temindung Permai, Tenun Samarinda)	90	8.22	71.34
5	Group 2 (Bugis, Bukuan, Gunung Panjang, Karang Mumus, Pasar Pagi, Pelabuhan, Pulau Atas, Sungai Kapih, Sungai Siring, Tanah Merah, Sindang Sari)	15	8.55	73.82
6	Budaya Pampang	2	5.95	64.00

Source: Seconday Data Analysis from Integrated Health Service Posts/*Posyandu* of Samarinda, 2023



Source: Seconday Data Analysis from Integrated Health Service Posts/*Posyandu* of Samarinda, 2023

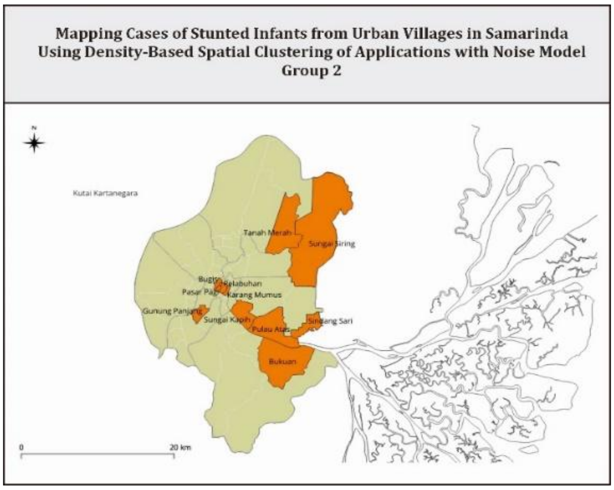
Figure 4. Mapping Results of Areas with No Group



Source: Seconday Data Analysis from Integrated Health Service Posts/*Posyandu* of Samarinda, 2023

Figure 5. Mapping Results in Group 1

There are eleven urban communities in Group 2 as seen in Figure 6. Bugis, Bukuan, Gunung Panjang, Karang Mumus, Pasar Pagi, Pelabuhan, Pulau Atas, Sungai Kapih, Sungai Siring, Tanah Merah, and Sindang Sari were the members of this group. Each area typically had around fifteen stunted babies. The fewer cases in Group 2 indicate that these areas may benefit from targeted, community-based interventions for early detection and prevention of stunting, might be more effective than large-scale nutritional campaigns.



Source: Seconday Data Analysis from Integrated Health Service Posts/*Posyandu* of Samarinda, 2023

Figure 6. Mapping Results in Group 2

DISCUSSION

The results of the DBSCAN model revealed two primary clusters. The unclustered villages, including Budaya Pampang, had the fewest cases. However, despite its lowest number of cases, Pampang Culture had alarming figures in terms of the average weight and height of stunted babies. These findings suggest that while stunting might not be widespread in Budaya Pampang, the severity of the cases there was much higher, indicating a localized but severe public health issue.

Spatially, Figures 4, 5, and 6 provided a clear visualization of the stunting distribution across Samarinda's urban villages. Harapan Baru, Sambutan, Loa Bakung, and all urban villages in Group 1 located in the central areas of Samarinda, had the highest numbers of stunted babies. This pattern was consistent with urban clustering of public health issues, where densely populated areas often face higher risks of malnutrition and stunting due to factors like overcrowding, limited access to healthcare, and inadequate nutrition. This is consistent with the results of previous studies showing that cases of stunted babies are more common in areas around urban centers kota.[11–14] Urban areas, especially densely populated ones, often face limited access to adequate health, sanitation and nutrition resources, which is a major factor in the high prevalence of stunting.[15–17] Furthermore, babies living in low-lying zones also tend to have a higher risk of stunting.[18]

Urban village like Bukuan, Pulau Atas, Sindang Sari and Sungai Kapih which are directly adjacent to the Mahakam River, have relatively fewer cases of stunted babies. This may be due to the greater availability of protein-rich processed fish, which was a crucial nutrient for preventing stunting, in these riverine areas. However, while fish consumption may be a protective factor, its effectiveness is strongly influenced by maternal nutritional parenting and family economic access. Families with good parenting tend to utilize natural resources such as river fish to meet their children's nutritional needs, while families with limited economic or nutritional knowledge may not be able to provide a balanced diet despite having access to protein sources.[19–22]

These findings emphasize the critical role of local socioeconomic factors, highlighting the need for a deeper investigation into community-level determinants of stunting. Qualitative research involving local residents and healthcare providers could uncover underlying challenges, such as cultural dietary practices, gaps in healthcare access, or economic constraints that quantitative data alone may not fully reveal. These insights would contribute to refining clustering models and tailoring interventions more precisely for each group.

Furthermore, integrating advanced machine learning techniques, such as ensemble methods or neural network-based clustering, holds promise for enhancing the predictive power. Such approaches may identify subtle patterns in the data that traditional clustering methods overlook, leading to more targeted and effective public health strategies.

CONCLUSION AND RECOMMENDATION

The DBSCAN model successfully grouped urban villages using health data from babies first 1,000 days. Using the optimal parameters (ε = 0.95, MinPts = 3), the analysis formed two clusters and identified four urban villages as outliers. These outlier urban villages, which showed significant variations in stunting cases, were designated as the highest priority for intervention. Based on the level of urgency, the top priorities were Kelurahan Harapan Baru, followed by Kelurahan Sambutan and Kelurahan Loa Bakung. This highlights how population density can be correlated with public health risks, such as malnutrition.

Based on these results, this study proposed key operational recommendations. For the urban villages with the highest priority outliers, the recommended actions are to investigate local root causes, deploy dedicated nutrition teams, and implement a monitored nutritional supplementation program. Subsequently, urban villages within Cluster 1 were identified as the second priority, requiring coordinated public health programs. The remaining cluster was deemed a lower priority but warrants ongoing monitoring. These targeted strategies ensure that resources are effectively allocated based on data-driven urgency.

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AUTHOR CONTRIBUTIONS

Conceptualization, methodology design, and data analysis by NAR; Conceptualization and Methodology design by A; Exploration data and processed geographic data by IKH; Coordinated the collection of stunting babies data from local Posyandu by M; Collected data by CFD and DS. The authors read and approved the final manuscript. NAR = Nanda Arista Rizki, A = Asyril; IKH = Isran K. Hasan; M = Maulidah; CFD = Carolina Fadia Dewi; DS = Dhira Syahlafandi.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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